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Image Segmentation Using Convolutional Neural Network Based Geodesic Active Contour Model for Deforestation at Iskandar Puteri

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Abstract
Deforestation has long been a continual environmental concern. Due to fast development and construction, this issue has become an increasingly significant, especially in Iskandar Puteri, Johor. To effectively address this issue, strategy such as an automated deforestation monitoring system is essential given the difficulties in determining the real extent of deforestation impact through human observations and the time-consuming nature of manually estimating deforested areas from raw satellite pictures. In this research, the curve evolution approach will be used on Geographic Information System (GIS) images where the affected area will be delineated. The Geodesic Active Contour (GAC) model was implied to detect the outline of the deforested area at the targeted location. To achieve high operational effectiveness, the model will integrate the Convolutional Neural Network (CNN) approach. Results show that the CNN-GAC based model can accurately quantify the deforestation while also visualize the chronological landscape change. The study seeks to provide valuable insights into the usage of the proposed model for accurately identifying and delineating deforestation areas, thus facilitating better monitoring and assessment of environmental changes in Iskandar Puteri. The real time events at the area are discussed to have high correlation to the deforestation.
Keywords: Deforestation; Geodesic Active Contour; Image Segmentation; Convolutional Neural Network.

Introduction

From originally surrounded by fishing village, Iskandar Puteri, Johor has undergone significant landscape changes in recent years due to construction projects such as Medini City, Forest City, and Smart City incentives. Rapid developments have led to increasing deforestation issue. The tree cover changes might not be easily identified by the bare eyes, hence there will be a need for science and technology in detecting it and one of the good tools to do so is image segmentation.

Image segmentation is an important process within the field of machine vision and image engineering task. It is a process of splitting the input image into groups according to useful information and similar characteristics [1]. Using computer visual analysis, the details of input data, which in this case will be the satellite images, can be compared at a clear vision and better understanding. By modern approaches, the time and effort required to identify the forest's border can be significantly reduced while also minimizing the risk of error [2]. Considering the important of accurate detection, the GAC model was chosen as the main method to be implemented with the integration with the deep learning technique of CNN approach.

The main purpose of this study is to address the critical deforestation issue in Iskandar Puteri, focusing on identifying the deforested areas through a series of integrated objectives. Firstly, it aims to investigate and refine the use of Convolutional Neural Networks (CNN) within the framework of the Geodesic Active Contour (GAC) model for enhanced image segmentation. Building on this investigation, the study seeks to develop a model that combines strengths of CNN and GAC algorithms to accurately detect and quantify deforested areas in the target area. Following the development phase, the next objective is to implement this algorithm within Python software, specifically targeting the processing and analysis of GIS images. Finally, the study intends to analyze and visualize the outcomes of this implementation, using numerical performance evaluation metrics to validate the effectiveness of the model. This comprehensive approach aims to provide a reliable and efficient tool for monitoring deforestation, facilitating better decision-making and conservation efforts.

Literature Review

Geodesic Active Contour

Within the field of image segmentation, the Geodesic Active Contour (GAC) model is a well-recognized and widely acknowledges nonlinear partial differential equation-based approach [3]. This model has many advantages such as it considered the input's general characteristics and can adjust to structural changes throughout the process of curve evolution . GAC models are also better compared to others as their ability to preserve the image's natural geometric properties by evolving contours. As the model incorporate principles from the Euclidean curve with shorter evolution, they will have a lower rate of convergence and are more immune to being bound by the local minima points [5]. The model has also shown to be flexible in solving various problems in different sectors such as medical image analysis[6], water boundary detection[7], vegetation patterns predictions[8] and more.

The main concept to the approach is the minimizer of the energy functional will give valuable output to the image segmentation task, where the basic energy functional is as shown.
Let $C(x): [0,1] \to R^2$ be a parametric curve.

$$\begin{aligned} E(C) &= E_{internal} + E_{eternal} \\ &= \alpha \int_0^1 |C'(x)|^2 \, dx + \beta \int_0^1 |C''(x)|^2 \, dx - \lambda \int_0^1 \left|\nabla I\big(C(x)\big)\right| dx \end{aligned} \tag{1}$$

Where the first two term represent internal energy, regulating the contour's smoothness, while the third term represent the external energy, guiding the contours towards the object's boundary [9].
The traditional level set based GAC method involves solving the level set evolution equation which is a PDE.

$$\begin{gathered} \frac{\partial u}{\partial t} = \mu g |\nabla u| div\left(g \frac{\nabla u}{|\nabla u|}\right) + v|\nabla u| g \quad on\ \Omega \times (0, \infty) \\ u(x,0) = u_0(x)\ on\ \Omega \end{gathered} \tag{2}$$

Where u represent the level set value, v is parametric active contour of snakes, ∇ is the gradient operator, g is a stopping function, Ω is the image domain and $|\nabla u|$ is to control the interior and exterior of contour [10].

Chan Vese model

The Chan-Vese (CV) model is a classical and well-known GAC model that was chosen to be compared with the proposed model. The model was said to have the advantage of clearing the false bright regions and can effectively detect weak edges in images while being resistant to noise. It is a region-based approach which operates by focusing on the differences in average image brightness between the inside and outside regions of the contour to identify the target area. This method does not rely on image gradients and, as a result, addresses some of the challenges associated with edge-based approaches [11]. The CV model has shown to have lesser variation, indicating the model will have less error and are more consistent[12]. When it comes to registration correctness, the model can also be improved to performs better than existing active contour models with the ability to reduce the noise[13].
The model is represented by a Mumford-Shah energy.

$$E(C) = \int C_i (I(x) - c_1)^2 dx + \int C_o (I(x) - c_2)^2 dx + v|C| \tag{3}$$

Where C is the curve to be fitted, where C_i and C_o are the regions inside and outside respectively. I is the image intensity, and c_1 and c_2 are the average intensity of image inside and outside respectively. [14]
To update the values of c_1 and c_2, the CV function can be rewrite in terms of the level set function with a predefined regularised Heaviside function as follow.

$$E(c_1, c_2, \varphi) = \alpha \int_\Omega \delta(\varphi(x))|\nabla\varphi(x)|dx + \beta \int_\Omega H(\varphi(x))dx + \lambda_1 \int_\Omega |f(x) - c_1|^2 H(\varphi(x))dx + \lambda_2 \int_\Omega |f(x) - c_2|^2 \left(1 - H(\varphi(x))\right) dx \quad (4)$$

Where the first term is the smoothing function; the second term expand the contour to enclose larger areas; the last two term measures the fitting of the average intensity for the region inside and outside the contour.

Convolutional Neural Network

Image processing is undergoing significant change as a result of the advancement of deep learning techniques and models [15]. The introduction to deep learning-based approaches has shown promising results by effectively capturing the important interpretation of the image and apply it as training sets for the model [16]. Models incorporating the Convolutional Neural Network (CNN) techniques has definitely shown to have great advantage as it handles the limitations of traditional approaches. It has shown great application in labelling and classification by learning the multilevel representations from the input which simplify the feature extraction [17]. Standard CNN models in the mainstream might show restricted adaptation in new circumstances and struggle to strike a balance between model size, inference speed, and accuracy. However, it was significantly less expensive computationally and does not require massive data for training [18].

Methodology

The data image to be used as the input was the screenshot of the latest satellite image at the Iskandar Puteri area found using the website Google Earth.

Algorithm The image segmentation process is implemented with coding on the Python platform. Some primary used libraries are OpenCV for computer vision and image processing, NumPy for calculations, Matplitlib for plotting the image, and TensorFlow to implement the deep learning techniques.The Chan-Vese algorithm started with preprocessing of the image by converting it to grayscale. The built in function of CV segmentation were used with maximum iteration of 100, and then converted to a binary image. The final segmented contour was drawn back on the original image.

Meanwhile for the CNN model with coding, the grayscale image was also used. The image was reformatted to apply the predefined convolution kernel, followed by the max pooling layer to condense the feature and the activation ReLU function to introduce nonlinearity. To produce a binary image that will later be used for segmentation, the processed image was scaled and transformed to a NumPy array. The final outputs were shown side by side for visual comparison, including the binary picture, the original grayscale image, and the image with contours drawn.

Result and discussion

Comparing two model

The GIS image used as input is the screenshot of satellite image of the Iskandar Puteri area from the website Google Earth. The segmentation of GIS satellite images of Iskandar Puteri was performed using the Chan-Vese model and the CNN-GAC algorithm. The results of visualization are as follows.

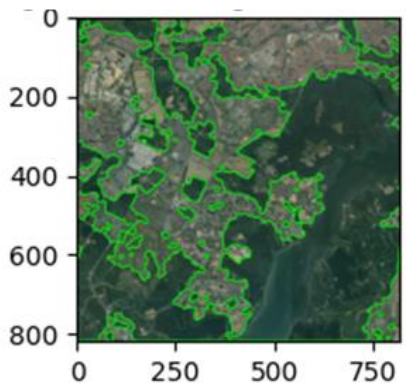

Figure 1 Segmented Image from Chan-Vese approach

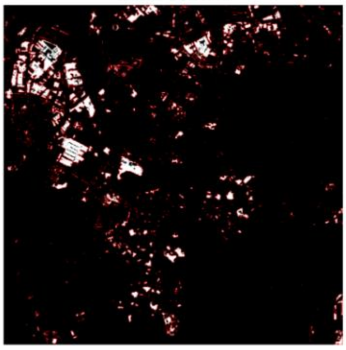

Figure 2 Segmented Image from CNN-GAC approach

To investigate the effectiveness of segmentation comparing between the Chan-Vese model and the CNN-GAC model, the few parameters were recorded for further analysis.

Table 1: The Performance Result between Chan Vese model and CNN-GAC model

Parameter	Chan-Vese Model	CNN-GAC model
Average Segmentation Run Time (s)	16.116236	0.018507
Size of image (pixels)	798 × 798	798 × 798
Total deforested area identified (pixels)	367248	92466.5
Percentage of deforested area	57.6705%	14.5204%
Depth of final contour	0.560796	22.886774

Figure 1 and 2 will be the segmented image by both model respectively, with the contour of CV model be in green line drawn on the original image and the contour detected by CNN-GAC model will be the red line drawn on the processed binary image. The white region in the CNN-GAC visualization represent the developed areas that are lack of tree covers. As for Table 1, will be the the analysis for both model under parameters such as average segmentation run time of 10 output, total deforested area identified, percentage of deforestated area, and the depth of final contour.

From Figure 1 and 2, it is clear to see that the segmented area contoured by the Chan-Vese model are larger than the area from CNN-GAC approach. Table 1 shows that the CNN-GAC model runs at a significantly slower time, demonstrating faster segmentation speed compared to the CV model. The CNN-based model has also identified a smaller deforested area in Iskandar Puteri, suggesting a more detailed detection comparing with the overestimation from Chan-Vese model. Additionally, the CNN-GAC model performs better in detecting details which are represented by higher value of the final contour's depth. This value denotes more uneven contour identification, which better reflects the curving boundaries of deforested areas.

Analyzing Historical Satellite images

The detection and analysing tools should be resilience to time. Hence, the two model were used to analyse historical satellite images from year 1985 to 2023. The data images were obtained from Google Earth Pro. The analysis will only focus on the deforested area detected and the percentage.

Table 2: Analysis on past satellite images

	Chan-Vese		CNN-GAC	
Year	Deforested Area (pixels)	Percentage (%)	Deforested Area (pixels)	Percentage (%)
1985	165879.5	40.50	4874.5	1.19
2011	258483	63.11	138706.5	33.86
2012	254994	62.25	92287.5	22.53
2015	200793	49.02	111826.5	27.30
2017	212990	52.00	170749	41.69
2018	184652.5	45.08	57202	13.97
2019	223382	54.54	64389	15.72
2020	182176	44.48	52897.5	12.91
2021	171097.5	41.77	57435	14.02
2022	180334	44.03	70199	17.14
2023	235736	57.55	60779	14.84

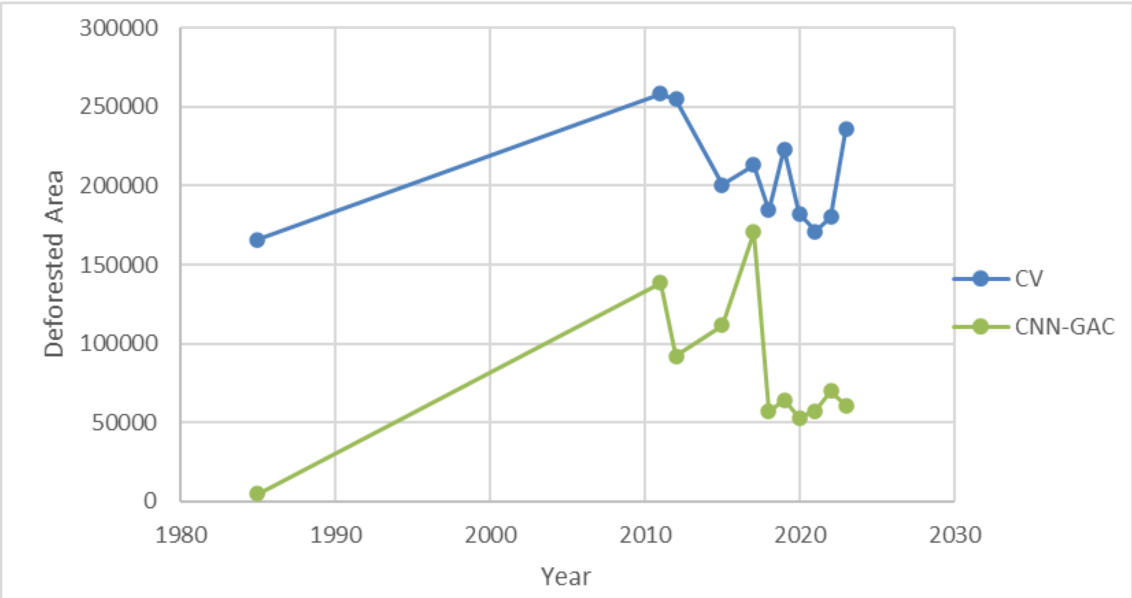

Figure 3 Deforested Area vs Year for CV and CNN-GAC model

As seen in Table 4.2 and Figure 4.4, the values recorded from the CV models are generally higher than that of the CNN-GAC model. The values from CV approach are somewhat questionable especially for the year 1985 with high deforested area detected at that time. On the other hand, the CNN-based model provides more logical results, reflecting the lack of development nor deforestation during that period. This suggests that the CV model only captures general boundaries without detailed detection like the CNN-GAC model.

Moving on, the discussion will focus on the CNN-GAC model's analysis of the past year's satellite images. Keeping in mind that the deforestation pattern recorded will reveal an ongoing dynamic influenced by the real-time situation there. The results show an increasing trend in deforested areas during the time between 1985 and 2011, peaking in 2017. This change is in line with Iskandar Puteri's development projects, particularly the one that intensified deforestation for various structures beginning in 2007. But after 2011, there are signs of reforestation efforts, especially with the introduction of projects such as "Green Iskandar Puteri" from Medini. The static trend after year 2017 indicating lagging in the development progress are said to be influenced by issues such as the Covid-19 pandemic, rumors of project failures, investment declines, economic and political issues.

Conclusion

In summary, integrating the CNN deep learning techniques with the classical GAC model shows potential improvement to enhance image segmentation. In comparison, the Chan-Vese model can delineate the deforested general boundary, while the CNN based model provides more precise detection. The model based on deep learning has proven to be more accurate at categorizing the objects in the GIS images. The deforestation patterns at Iskandar Puteri vary according to real time situations and are greatly influenced by urbanization policy, national economic situation, and political reasons. As a recommendation, reforestation should be prioritized in order to strike a balance between urban growth and conservation.

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